Sparse representation of channel's impulse response for underwater inhomogeneities tracking

Ion Candel, Cindy Bernard, Cornel Ioana, Bertrand Reeb, Didier Boldo

SPARSE REPRESENTATION OF CHANNEL'S IMPULSE RESPONSE FOR UNDERWATER INHOMOGENEITIES TRACKING

Ion Candel[1,2], Cindy Bernard[1], Cornel Ioana[1], Bertrand Reeb[2], Didier Boldo[3]

[1]GIPSA-lab, Grenoble Institute of Technology, 38402 Saint Martin d'Heres, France
E-mail: {Ion.Candel, Cindy.Bernard, Cornel.Ioana}@gipsa-lab.grenoble-inp.fr
[2]Electricite de France, Division Technique Generale, 38040, Grenoble, France
[3]Electricité de France, EDF R&D, 6 Quai Wattier, 78401, Chatou, France
E-mail : {Ion.Candel, Bertrand.Reeb, Didier.Boldo}@edf.fr

ABSTRACT

In this paper, we propose a method for underwater inhomogeneities characterization using sparse representation of channel's impulse response. We consider the case of moving vortices created naturally or artificially that do not conserve their physical properties when observed at two distinct positions in space. Existing amplitude–based techniques fail to provide an accurate representation when the physical properties of the dynamic inhomogeneity are altered, but it can be achieved using the decomposition of the inhomogeneity's impulse response, based on a physically driven decomposition basis. Tests carried out in a reduced scale experimental facility show, on real data, the efficiency of the inhomogeneities tracking.

Index Terms— sparse representation, underwater acoustics, inhomogeneity, decomposition.

1. INTRODUCTION

The dynamics of underwater phenomena can be understood as the propagation of vortices produced either naturally (natural inhomogeneity embedded in water flow, marine life such as fish and mammals) or artificially (underwater obstacles, submarines, vessels). These vortices are detected and analyzed using pairs of acoustic transducers. If a vortex intersects the path between two pairs of active transducers, the signatures observed on the received signal's amplitudes are quantifiable. However, specific phenomena associated to the context alter the signature when the inhomogeneity travels to another pair of transducers and thus the similarity between the two signatures is poor.

An alternative is to decompose the impulse responses corresponding to the two transducers pairs on basis of elementary functions. In order to adapt the basis to the context of our application, two concepts are studied in this paper. First, we propose to design a decomposition basis inspired by the physical characteristics of the vortex "seen' by the impulse response of two propagating acoustic paths.

The second concept is the one of the sparse representation [1]: the analyzed phenomena can be recovered only using some of the decomposition coefficients that are relevant with respect of the minimization criterion, thus obtaining a sparse representation of the phenomena. At this level, we show the interest of the L_1 norm.

The article is structured as follows: section 2 presents the theoretical concepts used in our work: waveform decomposition and sparse representation. Section 3 presents the main results and remarks of our work and section 4 presents the concluding remarks and future work.

2. DECOMPOSITION BY SPARSE REPRESENATION

The general layout of the analyzed phenomena is illustrated in figure 1. Wide band signals are transmitted using two pairs of sensors placed on the *Upstream* and *Downstream* sides.

In the absence of inhomogeneity (such as a vortex), there are no changes in the shape of the impulse responses of the channels defined by the two pairs of transducers. The apparition of the inhomogeneity between the transducers introduces modifications on the amplitudes of the impulse responses, calculated for each transmission, a fact that can be seen as *signatures* of the inhomogeneity's source (figure 2).

However, the vortex can change the characteristics while moving from one pair of sensors to the other, the similarity of the two signatures is low and can be considered as belonging to two different phenomena. This drawback can be eliminated using a decomposition of the two *signatures* based on a physically driven basis. That is, the decomposition attempts to highlight the common elements that will allow us to identify the inhomogeneity.

Considering the emitted signals from figure 1, $s_{e1}(t)$ and $s_{e2}(t)$, as two linear frequency modulations, described by the following equation:

$$s_{e1}(t) = s_{e2}(t) = Aexp\left[j\left(\omega_0 t + \frac{\gamma t^2}{2}\right)\right], \qquad (2.1)$$

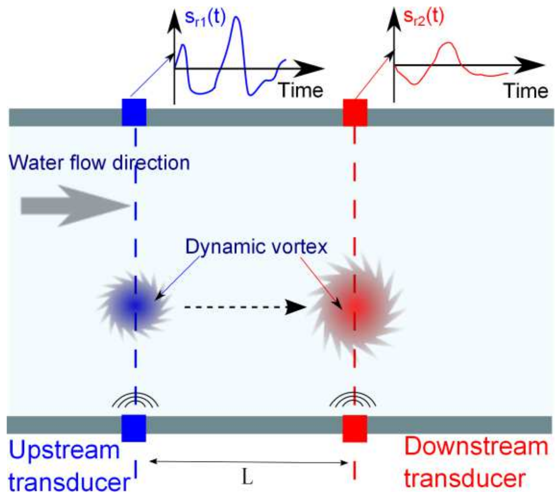

Figure 1. Vortex travelling with the flow of water

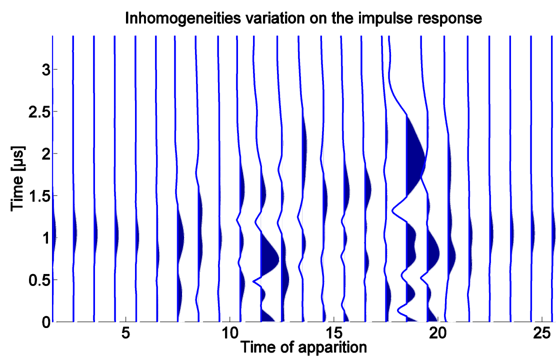

Figure 2. The signature of an inhomogeneity on the envelope of the impulse response.

where $\omega_0 + \gamma t$ is the linear frequency variation law. The received signals $s_{r1}(t)$ and $s_{r2}(t)$ for each transducer can be expressed, ignoring the noise, as:

$$s_{r1}(t) = A_{r1}(t) s_{e1}(t-\tau)$$
$$s_{r2}(t) = A_{r2}(t) s_{e2}(t-\tau), \tag{2.2}$$

where τ is the propagation time of the vortex between the emission and reception transducers. The envelopes A_{r1} and A_{r2} in equations (2.2) contain the information about the inhomogeneity evolution. We calculate the impulse response of the system for each transmission by correlating the received signal with the emitted one [2]:

$$h_{r1}(t) = \int_{-\infty}^{\infty} A_{r1}(t) \cdot s_{e1}(t-\tau) \cdot s_{e1}(t)\, d\tau$$
$$h_{r2}(t) = \int_{-\infty}^{\infty} A_{r2}(t) \cdot s_{e2}(t-\tau) \cdot s_{e2}(t)\, d\tau \tag{2.3}$$

As it can be seen from figure 2 (envelopes of impulse responses are shown for a better understanding of the phenomena), the *signature* left by a vortex is localized just after the main peak of the impulse response. However, the extraction of this signature must take into account the fact

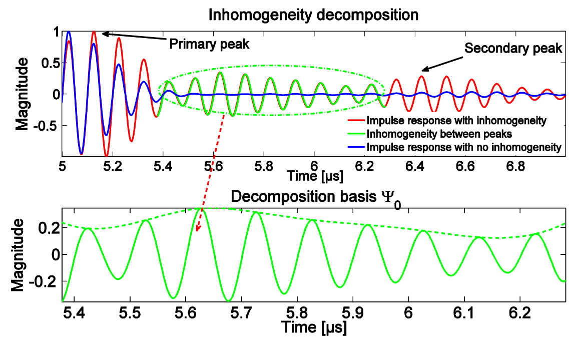

Figure 3. Decomposition principle of an inhomogeneity extracted from an impulse response.

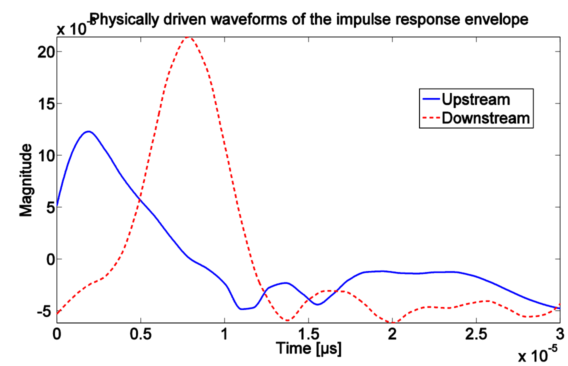

Figure 4. The contraction of the impulse response envelope due to the dynamic vortex.

that due to occurring reflection of echoes, a secondary much smaller peak appears (figure 3).

This representation of the signature (amplitude data) cannot reveal accurate amount of information regarding the physical properties of the vortex. Therefore, we propose the analysis via a decomposition using an appropriate basis function constructed from an *initial function* having an amplitude variation similar to the one introduced by the vortex (see figure 3).

The basic principle of the decomposition is illustrated, using real data, in figure 3. *Step one* of the sparse representation consists in constructing the elements of the initial basis which is the same for both $h_{r1}(t)$ and $h_{r2}(t)$, with a *zero mean and a rapid decrease*. The basis starts from an *initial waveform* ψ_0, which is a modulated sine wave centered on the resonance frequency of the transducers as illustrated in equation (2.4):

$$\psi_0(t) = A(t) \exp(j\omega_0 t), \tag{2.4}$$

where ω_0 corresponds to the resonance frequency of the transducers. The term *A(t)* represents the amplitude modulation produced by the dynamic vortex over the impulse responses. The choice of this term is based on the physics of the vortex: from one path to another, the envelopes are similar, but due to the heterogeneity induced by the vortex the shape of the envelope suffers a contraction in time (figure 4). Thus, the choice of $A(t)$ is made from the envelopes of the impulse responses that are affected the most by the inhomogeneity, in order to provide an physically adapted basis for the decomposition. As the inhomogeineity progresses through water, it keeps on enlarging due to its inertial character [3] and its energy decreases with distance.

Having defined the *initial waveform* we construct a set of functions that are shifted in time and scale, according to the continuous wavelet analysis, thus creating a dictionary of elementary functions, at different scales, shifted in time:

$$\psi_{s,u}(t) = \frac{1}{\sqrt{s}}\psi_0\left(\frac{t-u}{s}\right),\ s = 0.01 \cdot n;\ \ n = 1..N \quad (2.5)$$

where N is the maximum decomposition resolution, s and u are, respectively, the scale and shift parameters of the initial waveform ψ_0. The envelopes of the impulse responses from the *Upstream* side will be more contracted in time than the ones from the *Downstream* side. The reason for selecting the initial waveform among the impulse responses where the envelope's contraction is the highest resides in the decomposition process. The impulse responses will match the initial waveform ψ_0 at different scales highlighted by the s parameter in (2.5).

The representation that we wish to obtain for $h_{r1}(t)$ and $h_{r2}(t)$ can be written, using the resulting coefficients, as follows [4] :

$$h_{r1}(t) = \sum_{i=1}^{N} C^1_{s,u}\psi_{s,u}$$
$$h_{r2}(t) = \sum_{i=1}^{N} C^2_{s,u}\psi_{s,u}, \quad (2.6)$$

where $C^1_{s,u}$ and $C^2_{s,u}$ are the N resulting coefficients for the decomposition with the best ψ_i basis for the two impulse responses. The $C^1_{s,u}$ and $C^2_{s,u}$ coefficients represent the projection of the impulse function $h_r(t)$ on the ψ_i functions described in (2.4):

$$C^i_{s,u} = < h_{ri}, \psi_{s,u} > \quad (2.7)$$

The second step of the sparse optimization consists in minimizing the number of coefficients obtained from the decomposition. This is defined as a problem of minimization [1] with solutions derived from convex optimization [5].

In the case of the inhomogeneity estimation, a possible solution to the problem can be formulated as follows [6]: quantify the impact of each coefficient - basis pair between the two estimated inhomogeneitis, in our context, and minimize the number of coefficients needed to construct two signatures h^*_{r1} and h^*_{r2} with minimum errors.

Based on (2.6), we calculate a residual for each one of the N coefficients $(C^{i,j}_{s,u})$ and its corresponding basis:

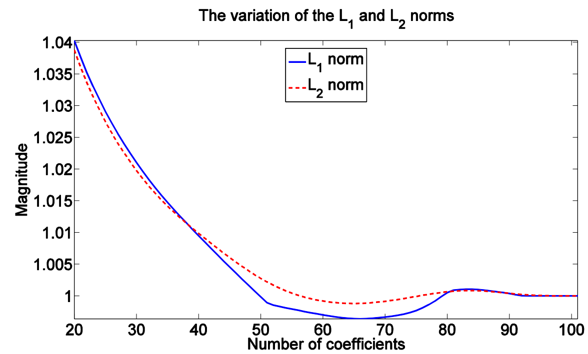

Figure 5. Variation of the L_1 and the L_2 norms.

$$R^i_P(t) = h_{ri} - \sum_{j=1}^{P} C^{i,j}_{s,u}\psi_{s,u}\ ,\ \ P, j = 1..N; i = 1,2 \quad (2.8)$$

where $R_P^j(t)$ is the residual calculated for the P^{th} coefficients of the decomposition.

In order to quantify the impact of each residual with respect to the decomposition and minimize the number of coefficients, we can use the L_1 or L_2 norm for each of the N residuals and select **only the *K*** coefficients corresponding to the number of coefficients for which the norm is minimum [7]. We choose to use the L_1 norm over the L_2 norm because the former leads to fewer coefficients than the latter (figure 5). The minima points of the L_1 norm correspond to the lowest number of coefficients used to represent sparsely the two signatures $\tilde{h}_{r1}$ and $\tilde{h}_{r2}$:

$$\tilde{h}_{r1}(t) = \sum_{i=1}^{P} C^1_{s,u}\psi_{s,u}$$
$$\tilde{h}_{r2}(t) = \sum_{i=1}^{P} C^2_{s,u}\psi_{s,u} \quad (2.9)$$

Since the basis of the decomposition is the same for both $\tilde{h}_{r1}$ and $\tilde{h}_{r2}(t)$, the two signatures will have a very strong resemblance, as it will be shown in the next sections.

3. RESULTS

The tests were carried out in our reduced scale experimental facility (figure 6). For our experiment, we used two pairs of 1MHz transducers placed on the outer walls of the tank. The length of the acoustic path was 1 meter at a depth of 40 cm.

Wide band signals were generated with a linear frequency modulation between 800 kHz and 1.2 MHz, and were downloaded into a signal generator for transmission. The repetition rate of the signals was 1msec and the duration of the wide band signal is of 200 microseconds in order to avoid the overlap of echoes over the received signals. First, the pairs of transducers had to be set apart by a certain

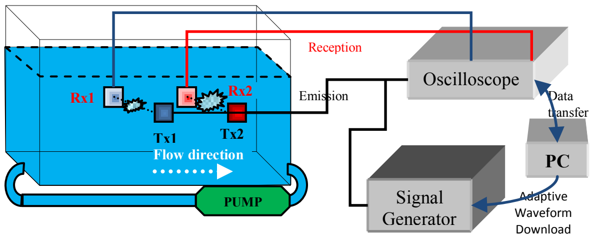

Figure 6. Reduced scale experiment test bench.

distance because of the occurrence of crosstalk caused by the wide beam angle of each transducer.

Reverberation was not an issue because water attenuation for 1MHz is high and the signal processing algorithms are capable to distinguish the received pings from echoes.

Water flow was created using the recirculation pump in order to provide a background inhomogeneity noise that would eventually superimpose over the simulated phenomena. Air was pumped through a tube submerged in the flow and the created inhomogeneity intersected the two acoustic paths.

The scale factor of *s* (decomposition basis parameter) was set to *0.01* due to resolution considerations and the *initial waveform* was selected among the zones extracted from the impulse response where the inhomogeneity had the strongest effect, thus creating a physically driven basis. Each received signal yielded a decomposition and a number of *K* coefficients was calculated using the L_1 norm. It was no surprise that except for the moments where inhomogeneity was at its strongest, the number of coefficients used for decomposition remained constant.

We compare our results in two ways: first, we show a significant improvement with a typical representation technique consisting in calculating the maxima values of the impulse response corresponding to each transmission as illustrated in figure 7. This technique is used extensively in certain flow metering applications presented in [8] and [9] and is sensible to interference induced by the measurement conditions.

Secondly, we use the results presented in figure 7 to calculate the average flow velocity between the acoustic paths. The accuracy of estimating the average velocity depends on the precision of estimating the time delay between the two acoustic paths. This is done by computing the cross correlation of the two signatures (*Upstream* and *Downstream*), as illustrated in figure 8 (a zoomed region displaying the main peaks of the two cross correlations).

In the second subplot of figure 8, we see an enhanced similarity between the signatures for the two acoustic paths, which describes an initial dynamic and random vortex. This result is possible only because of the physically driven basis that was used in the decomposition.

The second value (the real value calculated after the decomposition, highlighted on the red dotted trace with the vertical black line) corresponds to the correct orientation of

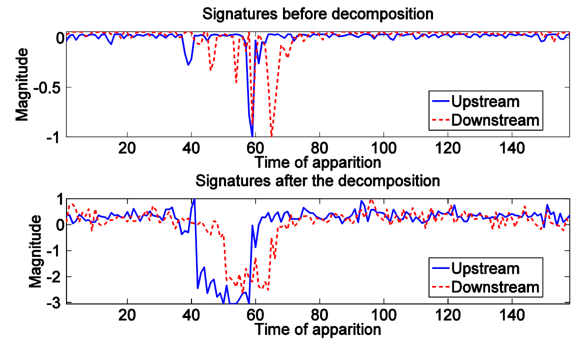

Figure 7. Inhomogeneity representation before and after the sparse decomposition.

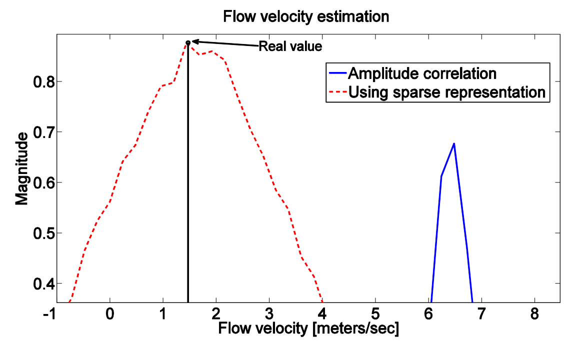

Figure 8. Flow velocity calculation using the cross correlation between the acoustic paths.

the flow and a more pertinent 1.47 meters/second flow velocity is computed. Using the average flow velocities from multiple levels over a square section output the values of flow on that section. This is a very sensitive problem as results from the existing methods are biased by unfavorable conditions.

It is very important to keep in mind that the simulated conditions aimed also at testing the limits of the algorithm in terms of robustness.

Figure 8 shows that, by comparing with the initial estimation in figure 7, the sparse representation manages to provide a correct estimation of a inhomogeneity translated in space.

The purpose of sparse representation, as shown in [7], was to recover a signal using minimum number of coefficients from incomplete and altered measurements.

The use of wide band signals in inhomogeneities tracking was introduced previously in [8] as an alternative to transmitting pulses in flow metering applications for obstacle path correction. It has been shown at the time that transmitting large band signals with a bandwidth around the central frequency of the transducers can improve the inhomogeneity derived flow metering estimation in case of large obstacles passing between the transducers. Additionally, in [9] we concluded that the inhomogeneity analysis would benefit from wide band signals in the case of low inhomogeneity levels and for this purpose, appropriate representation spaces are required in order to get invariant information about the inhomogeneity when “seen” from two (or more) spaced separated pints of view.

4. CONCLUSIONS

In this paper, we proceeded to demonstrate that sparse representation and adaptive decomposition techniques can be successfully used to recover a complete representation of inhomogeneity from incomplete and contaminated measurements (*sparse representation*).

A small scale experiment consisted in generating inhomogeneity was carried out and wide band signals were used to highlight the passage of the inhomogeneity at two separated acoustic paths, all in the least favorable conditions.

Results obtained with our technique prove the theoretical concepts of sparse representation and adaptive waveform using large band signals.

Our work will focus in the future on combining adaptive waveform techniques with sparse representations aiming at finding a signal that is appropriate to underwater inhomogeneity estimation using an orthonormal decomposition basis.

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